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Will the Crisis Affect the Economic Recovery in Eastern European Countries?

Evidence from Firm Level Data

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Abstract

Two sources of growth are firm learning and innovation. Using a unique panel data for 1,686 firms in six countries (Bulgaria, Hungary, Latvia, Lithuania, Romania, and Turkey), this paper applies panel data estimators and Juhn-Murphy Pierce decomposition in order to identify the effects of the global economic crisis on sales growth of innovative and young enterprises in Eastern European countries. The results show that innovative and young firms were significantly more affected by the crisis than non innovative and older enterprises. The authors interpret these results as an indication that the achievement of pre-crisis growth rates in those countries may be difficult.

This paper—a product of the Private and Financial Sector Development Sector Unit, Europe and Central Asia Region—is part of a larger effort in the department to study the effects of the financial crisis on the corporate sector. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The author may be contacted at pcorrea@worldbank.org.

WILL THE CRISIS AFFECT THE ECONOMIC RECOVERY IN EASTERN EUROPEAN COUNTRIES? EVIDENCE FROM FIRM LEVEL DATA[1]

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1 - Introduction

One question of the current international debate particularly relevant to Eastern European countries refers to the potential drivers of the economic recovery. As international trade declines and financial conditions worsen, firm learning and innovation become more relevant sources of growth in the post-crisis period. Conditional on size and survival rate, young firms are expected to grow faster than older firms, among other reasons, due to diminishing returns to learning (Klepper and Thompson (2007); Dunne, Roberts and Samuelson (1989)). Innovative firms are also expected to provide a positive contribution to economic growth, as innovation and R&D tend to positively affect firm-productivity and sales performance (Aw, Roberts and Xu (2008)).[2] In this sense, understanding how the crisis will affect innovative and young enterprises helps comprehends Eastern European growth prospects.

In this paper, we investigate the sales growth of innovative and young firms in the region, before and after the crisis. We apply two methods. First, we use panel-data estimators in order to assess the difference of sales growth performance between innovative (young) and non-innovative (older) companies, over the period, when controlling for firm characteristics. Second, we use the Juhn-Murphy-Pierce technique to decompose the difference in sales growth performance between those groups of firms, before and after the crisis, into: i) differences in the distribution of observed characteristics (the characteristics effect); ii) differences in the "market value" of such characteristics (the returns effect); and iii) differences in unobservable attributes and "market values" (the unexplained effect). This decomposition technique not only allows us to check the econometric findings but also helps us to assess the sources of sales differentials between those firms' cohorts.

Panel data analysis shows that sales growth rate of innovative firms have declined more than that of non-innovative companies, a result that is robust regardless the estimator applied, and the criteria used to categorize innovation (introduction of a

2 The micro-macro link between firm-level innovation, theories of aggregate technological change and growth can be found in Klette and Kortum (2004).

product/process, or development of R&D activities). Our analysis also points that the decrease of sales growth rate of younger firms was more severe than older companies. The decomposition exercise confirms that the positive difference of sales growth rate in favor of innovative and in favor of young companies, before the crisis, was reversed afterwards. For innovative companies, we found evidence that the reduction in the "premium" for the ability to innovate – which we interpret as Schumpeter's "animal spirit" – after the crisis contributed to explain the worse performance of innovative firms. Conversely, in the case of young enterprises, results suggest that their "ability to learn" contributed to mitigate the negative impact of the crisis on sales growth performance. Overall, we interpret these results as indication that the achievement of pre-crisis growth rates in those countries may be difficult.

The paper is organized as follows. The next section describes the data used and exposes the empirical methodology applied. Section 3 presents results on the empirical analysis, and Section 4 summarizes the main results.

2 – Data and Methodology

We use a unique panel data for 1,686 firms in six countries (Bulgaria, Hungary, Latvia, Lithuania, Romania, and Turkey) covering manufacturing, retail and other service sectors.[3] This panel results from the matching of two datasets. The first one is the World Bank's Financial Crisis Survey (EFCS) - implemented in June/July 2009 and designed to capture the effects of the crisis on key elements of the private economy: sales, employment, finances, and expectations about the future. The second one is the World Bank's Enterprise Survey (ES) carried out in 2008. With an original sample that is stratified by firm size, sector and region and representative of the private nonagricultural formal economy in each country, the ES 2008 provides information on firm characteristics, various performance measures and the business environment, most of them refereed to fiscal year of 2007, the pre-crisis scenario. The merger between the two datasets was possible since the EFCS covers a subsample of firms drawn from the set of firms interviewed in the ES 2008. As the participation in EFCS was voluntary and the entire original sample of the ES, which covered

[3]Turkey is the exception, where only the original manufacturing subsample was targeted.

2,499 firms, was contacted to determine whether these firms were still in existence or if they had failed and/or became inactive, the sampling weights of the ES 2008 were adjusted, based in the non-response firms. These adjusted weights were then used in order to produce the estimations that are, therefore, representative for the nonagricultural private economy within each country.

We classify the firms into groups of: i) young and older firms; and ii) innovative or non-innovative companies. To distinguish the age status of the firm, we define a dummy $Young_i$ for firms up to five years old in before (2007) the crisis. To distinguish the innovative status of the firm, we used as a criterion the introduction of new product or process in the period 2005-2007, according to ES 2008.[4] As we do not have this information for 2009, we then define a dummy $Inov_i$ that equals one if the firm has introduced a product/process in 2005-2007 period, and repeat this value for the post-crisis period.[5] Alternatively, we use as a criterion to classify innovative companies the development of R&D activities in 2005-2007 period, also according to ES 2008.[6] Table 1 presents the estimated proportions of innovative and non-innovative companies across countries, following the two criteria, while Table 2 shows the estimated proportions of firms by age. Non-innovative firms as well as older firms make the largest groups in all countries.

[4]The question used in ES 2008 was "In the last three years, has this establishment introduced new products or services?"

[5]Therefore, even though we recognize that innovation process is not static over time, we work with an innovation category that is time invariant, as we assume that innovative firms in the precrisis scenario (2004-2007) are potentially innovative after the crisis (2009).

[6]The question used in ES 2008 was "In the last three years, has this establishment invested in research and development (in-house or outsourced)?"

Table 1 – Proportions of innovative/noninnovative companies, by country

	Noninnovative	Innovative	
Country	**Did not introduce new product/process**	**Introduce of new product/process**	**N. Obs**
Turkey	0.60	0.40	513
Romania	0.51	0.49	365
Hungary	0.66	0.34	187
Latvia	0.43	0.57	226
Lithuania	0.34	0.66	238
Bulgaria	0.50	0.50	149
Total	0.52	0.49	1,678
Country	**Did not invest in R&D**	**Invested in R&D**	**N. Obs**
Turkey	0.70	0.30	513
Romania	0.77	0.23	359
Hungary	0.90	0.10	187
Latvia	0.84	0.16	225
Lithuania	0.86	0.14	239
Bulgaria	0.63	0.37	150
Total	0.76	0.24	1,673

Source: EFCS 2009-ES 2008

Table 2 – Proportions of young/older companies (before the crisis), by country

Country	Young (< = 5 years old)	Older (>= 6 years old)	N.obs
Turkey	0.11	0.89	514
Romania	0.20	0.80	370
Hungary	0.11	0.89	187
Latvia	0.17	0.83	226
Lithuania	0.25	0.75	239
Bulgaria	0.11	0.89	150
Total	0.11	0.89	1,686

Source: EFCS 2009-ES 2008

Using the innovation and age groups defined above, we examine a particular measure of firm performance: growth in sales. We calculate the sales growth rates before and after the crisis (Table 3) for these categories of firms. For the pre-crisis period, we use the sales value of 2007 fiscal year and three years before that, from ES 2008, and compute the annualized growth rate of sales in the 2004-2007 period.[7] For the post-crisis period, we use annual growth rate of sales in the 2008-2009 period[8], according to EFCS.[9]

[7] Sales values for 2004 and 2007 were originally in local currencies and were converted to current US dollars using exchange rate from International Financial Statistics Database. We then controlled for outliers of sales

Table 3 - Sales Growth Rates (in %) comparisons: before and after the crisis

	Precrisis			Postcrisis		
	Average	95% Conf. Interv.		Average	95% Conf. Interv.	
Innovative (introduce new product/process)	36.38	*27.05*	*45.71*	-26.48	*-29.68*	*-23.29*
Noninnovative (did not introduce new product/process)	23.39	*16.70*	*30.07*	-25.34	*-28.46*	*-22.22*
Innovative (invest in R&D)	45.29	*27.87*	*62.71*	-27.02	*-31.82*	*-22.21*
Noninnovative (did not invest in R&D)	24.61	*19.76*	*29.45*	-25.55	*-28.08*	*-23.02*
Young (< = 5 years old)	45.52	*28.10*	*62.94*	-30.13	*-36.77*	*-23.48*
Older (>= 6 years old)	26.90	*20.97*	*32.84*	-25.42	*-27.78*	*-23.06*

Source: EFCS 2009- ES 2008

Data shows that before the crisis, growth rates for innovative (young) firms showed to be significantly higher than non-innovative (older) companies, at 5% level of significance.[10] After the crisis, however, the reduction in growth rate was higher for innovative (young) firms, though not statistically significant. These results seem to suggest that the crisis impact was higher for innovative and young companies. However, besides lacking of statistical significance for the comparisons after the crisis, these results reflect only a partial analysis. One can argue whether the difference of sales growth performance between the refereed groups of firms persist when controlling for other firm characteristics that are likely to affect sales performance.

In order to address this, we apply an empirical approach to discuss to what extent innovative (young) firms were more affected by the global downturn once firm idiosyncratic characteristics are taken into account. Two empirical methods are used.

values for both 2004 and 2007. The criterion was to consider as an outlier the observations lying outside the interval defined as the average ± three standard deviations of the refereed variable expressed in logarithm form.

[8] June/July 2008 to June/July 2009. As the 2008/2009 growth rate ranges from -100% to 100%, we didn't control for outliers.

[9] Some World Bank reports (like the EU10 Regular Economic Report) state that the acute phase of the crisis in these countries was in the second half of 2008 (specifically September 2008), but the severity of the impact was perceived only in 2009 statistics, even though the economic activity has stabilized in the second half of 2009. As we only have data for June/July 2009, we just use this point as a postcrisis reference.

[10] For the precrisis comparison between innovative and noninnovative companies, the results are valid regardless the criteria used to classify innovative companies.

First, we apply a panel-data analysis in order to assess the difference of sales growth performance between innovative (young) and non-innovative (older) companies, from pre to post-crisis period, when controlling for certain firm characteristics.

This panel analysis uses the specification listed in Equation 1. Annual growth rate of sales of firm i at two (t=2) time periods (2004/2007 and 2008/2009) is represented by g_{it}.[11] $Small_{it}$ (11-50 full time employees), $Medium_{it}$ (51-250) and $Large_{it}$ (≥251) stand as controls for firm size in the two periods. [12] The omitted category is $Micro_{it}$. $Export_{it}$ is another firm-level control variable; it is a dummy distinguishing firms that generate more than 10% of their sales from exports.[13] Sector_t and $\mathrm{country}_t$ control for the 2-digit industry and the country of the firm.[14] As already defined, $Young_i$ is a variable controlling for firm age in the pre-crisis period. The variable Inov_i reflects, as stated earlier, the innovative status of the firm. Skill_i depicts the use of skilled workforce by the firm; it is a dummy defined as more than 20% of employees with university degree in 2007, the pre-crisis period. As it happens with the Inov_i variable, due to lack of data to reflect the use of skilled workforce by the firm in the 2008/2009 period, we repeat the value of Skill_i in t=2 as the same as in t=1.[15]

As we are interested in examining how the sales growth performance of innovative/non-innovative firms and of young/older companies have evolved over time, we interact $Inov_i$ and $Young_i$ with a time trend variable (we do the same for $Skill_i$). Equation 1 is then defined as:

$$g_{it} = \beta_0 + \beta_1 t + \beta_2 Inov_i + \beta_3(t * Inov_i) + \beta_4 young_i + \beta_5(t * young_i) + \\ + \beta_6 Skill_i + \beta_7(t * Skill_i) + \theta Z_{it} + u_{it} \qquad (1)$$

[11]As already stated, for the precrisis period, we use the annualized growth rate of sales in the 2004-2007 period, based on data from ES 2008. For the postcrisis period, we use annual growth rate of sales in the June/July 2008- june/july 2009 period, according to EFCS.
[12] Specifically, the dummy size variables for the two periods (t=1 and t=2) are defined based on information of, respectively, 2007, from ES 2008, and 2009, from EFCS 2009.
[13] The dummy of export orientation for the two periods (t=1 and t=2) are defined based on information of, respectively, 2007, from ES 2008, and 2009, from EFCS 2009.
[14] While controlling for industry fixed effects we can account for any factor that can create heterogeneity across industries, as differences in the level of competition and in technology use. Meanwhile, country fixed effects allows to isolate potential differences in macro policies that may affect the evolution of firms in each country. The omitted categories are "other manufacturing" sector and Bulgaria, respectively.
[15] Therefore, the variable $Skill_i$ is also time-invariant, and reflects, in the postcrisis period, the potentially skilled intensive firms.

where Z_{it} is a vector of control variables representing size, export orientation, country and sector, as previously defined. The error term u_{it} is defined as:

$$u_{it} = \alpha_i + \varepsilon_{it} \qquad (2)$$

where α_i are *random* individual-specific effects and ε_{it} is an idiosyncratic error. Following a random effect model, both α_i and the idiosyncratic error are assumed to be uncorrelated with regressors. We use two different estimators for this random effect model: the FGLS (feasible generalized least squares estimator) and the PFGLS (pooled feasible generalized least squares estimator), also called population-averaged estimator. The difference between them is related to the assumptions about the structure of serial correlation of the model error, u_{it}. While the FGLS restricts this serial correlation to be the same at all lags (so the errors are called equicorrelated), the PFGLS estimator here applied places no restriction on the error.[16] Both of the estimators obtain cluster robust standard errors and use probability weights in order to get results that are representative for all firms in each country.

The second empirical method to be used is the Juhn-Murphy-Pierce (JMP) decomposition. This technique was first employed by Juhn, Murphy and Pierce (1993) and applies micro-simulation techniques to decompose the differences between two outcomes distributions (from previous OLS fitted results) for two population sub-groups.[17]

Following Juhn, Murphy, and Pierce (1993) the framework is then defined. First, after estimating an OLS model to explain the sales growth rate of two population sub-groups separately (let's assume, for instance, the innovative and non-innovative companies) in one given period (for instance, before the crisis), we define two models:

[16] Let $\rho_{ts} = Cor(\mu_{it}\mu_{is})$ be the error correlation over time for individual i, the FGLS estimator sets $\rho_{ts} = \rho$ for all $s \neq t$ so that errors are assumed to be equicorrelated. The population-averaged estimator (PFGLS) we use places no restriction on ρ_{ts}.

[17] This method is a variant of the classical Oaxaca and Blinder decomposition technique, widely applied in labor economics to explain wage differentials between groups of workers (Oaxaca, 1973 and Blinder,1973) When compared to Oaxaca-Blinder method, the JMP decomposition technique has the distinct advantage of dealing explicitly with the residuals from the estimation, therefore considering three components (characteristics, return and unexplained effects), while Oaxaca-Blinder deals with only two (characteristics and return effects).

$$y_1 = x_1\beta_1 + u_1 \qquad (3)$$

$$y_2 = x_2\beta_2 + u_2 \qquad (4)$$

where 1 and 2 set the innovative and non-innovative groups of firms; y_1 and y_2 are the vectors of the values of the dependent variable - sales growth rate - in the two firms' groups; x_1 and x_2 are the data matrices (observed characteristics)[18] for the two firms' groups; β_1 and β_2 are the vectors of estimated coefficients (observable returns – "market values" of those characteristics) for the two sub-groups; and, u_1 and u_2 are the vectors of estimated residuals (unobservable, i.e., unmeasured characteristics and returns) for the same sub-groups.

Let $F_1(.)$ and $F_2(.)$denote the cumulative distribution functions of the residuals for innovative and non-innovative groups, respectively. Therefore, if we take

$$p_{i1} = F_1(u_{i1}|x_{i1}) \qquad (5)$$

to be the percentile of an individual firm's (i) residual in the residual distribution of innovative firms, we can write:

$$u_{i1} = F_1^{-1}(p_{i1}|x_{i1}) \qquad (6)$$

where $F_1^{-1}(.)$is the inverse of the cumulative distribution function for the "innovative firms" group. The same procedure can be done to write the individual residual in the residual distribution of non-innovative companies.

Next, assume that $\overline{F(.)}$ to be the reference residual distribution (e.g., the average residual distribution over both samples) and let $\bar{\beta}$ to be an estimate of benchmark coefficients (e.g, the coefficients from a pooled model over the two firms' groups. Based on

[18] Both the theoretical and the empirical literature suggest that attributes like human capital, size, age, and export orientation are likely to affect firm evolution. Klette and Kortum (2004), Aw, Roberts and Xu (2008), Seker (2009) and Bernard et al (2007) are some examples. Therefore, when comparing innovative and noninnovative companies, the set of observable characteristics that influences sales growth includes the following variables: size (dummies of 1-10 full time employees,11-50, 51-250 and ≥251), firm age (a dummy for firms up to five years old), use of skilled labor (a dummy for firms with more than 20% of employees with university degree in 2007), export orientation (a dummy distinguishing firms that generate more than 10% of their sales from exports), country and sector fixed effects. For the comparison young and older firms, the set of characteristics includes: size in the period, innovation status (a dummy distinguishing companies that have introduced a new product/process in the 2004-2007 period), use of skilled labor in the precrisis period, export orientation in the period, country and sector fixed effects.

this framework we can construct hypothetical outcome distributions with any of the three components held fixed. We can then determine:

(A) hypothetical outcomes with varying observable characteristics but fixed coefficients and fixed residual distribution as

$$y_{i1}^{(A)} = x_{i1}\bar{\beta} + \overline{F^{-1}}(p_{i1}|x_{i1}) \qquad (7)$$

$$y_{i2}^{(A)} = x_{i2}\bar{\beta} + \overline{F^{-1}}(p_{i2}|x_{i2}) \qquad (8)$$

(B) hypothetical outcomes with varying observable characteristics and varying coefficients but a fixed residual distribution as

$$y_{i1}^{(B)} = x_{i1}\beta_1 + \overline{F^{-1}}(p_{i1}|x_{i1}) \qquad (9)$$

$$y_{i2}^{(B)} = x_{i2}\beta_2 + \overline{F^{-1}}(p_{i2}|x_{i2}) \qquad (10)$$

(C) outcomes with varying observable characteristics, varying coefficients and varying residual distribution as

$$y_{i1}^{(C)} = x_{i1}\beta_1 + F_1^{-1}(p_{i1}|x_{i1}) \qquad (11)$$

$$y_{i1}^{(C)} = x_{i1}\beta_1 + F_1^{-1}(p_{i1}|x_{i1}) \qquad (12)$$

These last outcomes are actually equal to the originally observed values:

$$y_{i1}^{(C)} = y_{i1} = x_{i1}\beta_1 + F_1^{-1}(p_{i1}|x_{i1}) \qquad (13)$$

$$y_{i2}^{(C)} = y_{i2} = x_{i2}\beta_2 + F_2^{-1}(p_{i2}|x_{i2}) \qquad (14)$$

Let a capital letter stand for a summary statistic of the distribution of the variable denoted by the corresponding lower-case letter. For instance, Y may be the mean of the distribution of y. So, the differential $Y_1 - Y_2$ can be decomposed as:

$$Y_1 - Y_2 = \left[Y_1^{(A)} - Y_2^{(A)}\right] + \left[\left(Y_1^{(B)} - Y_2^{(B)}\right) - \left(Y_1^{(A)} - Y_2^{(A)}\right)\right] + \left[\left(Y_1^{(C)} - Y_2^{(C)}\right) - \left(Y_1^{(B)} - Y_2^{(B)}\right)\right] \qquad (15)$$

$$= T = C + R + U$$

where T is the total difference; C can be attributed to differences in observable characteristics - the characteristic (or quantity) effect; R to differences in observable returns – the return (or price) effect, and U to differences in unobservable quantities and returns – the unexplained (or residual) effect.

In this paper, as we are using the JMP method to analyze the difference of sales growth performance distribution between the two groups of firms, the first component - characteristics (or quantity) effect - captures the part of the difference of sales growth performance between the two groups of firms that is due to differences in observable characteristics (quantities). In other words, it quantifies to what extent innovative (young) firms have a more favorable "endowment" in terms of observable characteristics as compared to non-innovative (older) companies. For example, one firm category might have, on average, larger firms, larger use of skilled workforce and larger export orientation, and these might lead to higher growth sales performance.

The second component, the return (or price) effect, reflects the part of the gap of sales growth performance between the two groups of firms that is due differences in returns of those observable characteristics. In other words, it measures to what extent the returns of those observable characteristics on the sales performance of a firm differ between innovative (young) and non-innovative (older) companies. For example, one firm category might get larger returns from the same observable characteristics when compared to other firm group.

The third component, the unexplained (or residual) effect, measures the part of the difference of the sales growth performance between the two groups of firms that is due to differences in unobservable characteristics and returns or to measurement error. Assuming that the OLS models that explain sales performance of the two companies' cohorts are satisfactorily specified, any unmeasured factors that affect the performance of these two groups will be capture by this residual effect.[19] For the comparison between innovative and non-innovative firms, we interpret this residual effect as a reflection of the difference between the two firm cohorts in terms of some intangible assets, such as the specialized knowledge embodied in researchers, the firms' entrepreneurship ability or its "animal spirits". When comparing young and older firms, this residual effect could measure

[19] As already stated, the choice of the variables used in the OLS models that explain the sales growth rate of the two groups of firms draws on the theoretical and empirical literature of firm evolution.

those firms' intangible assets related to age, such as the ability to appropriate of learning benefits.

3 – Main Results

3.1 – Panel Data Analysis

The regression results for Equation (1) are given in Table 4. Both the FGLS estimator and the population-averaged estimator (PFGLS) results are displayed.[20] The relevant parameters to be examined in both of the results sets are those related to the following variables: i) time interactions with innovative status of firm ($t * Inov_i$) and with the age status of the firm ($t * young_{it}$); and ii) time dummy.

The coefficients associated to time interactions variables basically represent the difference in the changes of sales growth rate between the two categories over time. In other words, it provides the predicted sales growth variation of innovative (young) firms, compared to non-innovative (older) companies, over time (i.e, from pre-crisis to post-crisis period).[21] Meanwhile, the dummy variable aims to reflect the aggregate difference in growth sales performance of all firms before and after the crisis when controlling for firm characteristics. This could be assumed as a proxy of the aggregate crisis impact on the enterprise performance in these countries.

[20] Before presenting the results, it is worth noting that these estimators have shown to be consistent; the Hausman test presented evidence in favor of the random effect model. The overall statistic of the Hausman test (which assumed the null hypothesis that random effect estimator was fully efficient) was: Prob>Chi2=0.9726.

[21] For example, for the innovative/noninnovative comparison, the coefficient associated to the interaction variable ($t * Inov_i$) represents the difference-in-difference estimate, as defined as:

$$\delta = \left[(g_{IN,t} - g_{NonIN,t}) - (g_{IN,t-1} - g_{NonIN,t-1}) \right]$$

where $g_{IN,t}$ is the growth sales rate of innovative companies in the postcrisis period – 2008/2009, and $g_{IN,t-1}$ is the annualized growth sales rate of innovative companies in the precrisis period – 2004/2007. For noninnovative companies $g_{NonIN,t}$ and $g_{NonIN,t-1}$ are the growth sales rate in the postcrisis and precrisis periods, respectively. It is important to distinguish the interpretation of ($t * Inov_i$) coefficient from the interpretation of $Inov_i$'s coefficient. While the last coefficient measures the difference between the average sales growth rates of innovative and noninnovative companies over time, the coefficient associated to ($t * Inov_i$) measures the difference in the changes of sales growth rate between the two categories over time. For instance, if the coefficient of $Inov_i$ is positive, this would mean that, on average, the growth rate of innovative firms is larger than noninnovative companies. A negative sign for the coefficient of $t * Inov_i$ would not contradict this; it would mean that, over time, the decrease in the sales growth rate of innovative companies has been larger when compared to the decrease in sales growth rate of noninnovative companies.

The results in columns 2 and 3 showed that when controlling for firm-specific characteristics, innovative firms have performed significantly worse than non-innovative companies over the refereed period (from pre-crisis to post-crisis period).[22] The pooled FGLS estimator revealed that the sales growth rate of innovative companies has decreased 15.97 percentage points more than the sales growth rate of non-innovative over time, at 5% level of significance. The FGLS estimator confirms this result as it shows that the contraction in the sales growth performance of innovative companies was 16.31 points larger than the growth performance of non-innovative firms, also at 5% level of significance.[23]

In order to examine if these results are robust to the way innovative firms are classified, we re-estimate the sales growth equation using the development of R&D activities in the 2004-2007 period as an alternative criterion to categorize innovative firms (see columns 4 and 5). The population-averaged estimator showed that, when comparing the pre and post-crisis periods and controlling for firm-specific characteristics, the sales growth performance of companies with R&D activities has decreased 25.34 percentage points more than firms without R&D activities; this difference was statistically significant at 1% level. The FGLS estimator also reveals that firms with R&D activities performed worse over time, though without statistical significance.

[22] Even though innovative companies have presented larger negative changes of sales growth rate over time, they did grow more than noninnovative firms, on average (see result for $Inov_i$ variable).

[23] To check whether possible correlations between innovation and export orientation variables could influence the results, we applied the population average estimator to three different specifications: i) Equation 1 including $(t * Inov)_i, (Inov_i)$, $(Export_{it})$, and $(t * Export_{it})$ variables; ii) Equation 1 including $(t * Inov)_i$, and $(Inov_i)$ variables; and iii) Equation 1 including $(Export_{it})$ and $(t * Export)_{it}$ variables. The results, presented in Tables II and III in the Annex, showed that the inclusion of export related variables - $(Export_{it})$ and $(t * Export_{it})$- do not change the fact that innovative companies have performed significantly worse than noninnovative companies over time, which always showed to be statistically significant. Besides, the results of $(Export_{it})$ and $(t * Export_{it})$ have never presented statistical significance, regardless the specification used.

Table 4 – Explaining the sales growth rate over time: a panel data analysis*

	Innovation measured as introduction of product/process		Innovation measured by the performance of R&D	
Coefficient	**pooled FGLS estimator (2)**	**FGLS estimator (3)**	**pooled FGLS estimator (4)**	**FGLS estimator (5)**
time	**-47.273*** **	**-47.728*** **	**-48.740*** **	**-54.442*** **
	(3.676)	**(4.601)**	**(3.305)**	**(4.715)**
innovative	14.229**	15.603**	22.022**	5.200
	(6.357)	(6.834)	(9.618)	(7.599)
time X innovative	**-15.975** **	**-16.316** **	**-25.345*** **	**-5.160**
	(6.717)	**(6.890)**	**(9.398)**	**(7.694)**
Young	18.775**	19.490***	18.453**	18.628***
	(9.498)	(7.004)	(9.071)	(7.027)
time X young	**-17.623* **	**-20.679*** **	**-17.446* **	**-19.782*** **
	(10.042)	**(7.410)**	**(9.675)**	**(7.449)**
skilled-intensive	-7.805	-13.336**	-7.538	-11.392**
	(5.970)	(5.343)	(5.475)	(5.030)
Time X skill	12.174*	13.089**	12.431**	10.663**
	(6.288)	(5.540)	(5.960)	(5.190)
Small	6.818**	7.046***	7.703**	7.726***
	(3.337)	(2.528)	(3.193)	(2.503)
Medium	11.141***	11.299***	11.553***	12.059***
	(4.115)	(3.738)	(4.244)	(4.128)
Large	7.243*	11.090***	7.267*	12.064***
	(4.028)	(3.339)	(4.180)	(3.650)
Export-oriented	-6.502*	-4.264	-6.859*	-3.794
	(3.726)	(3.754)	(3.783)	(3.647)
_cons	12.069**	16.063***	12.097***	21.291***
	(4.734)	(5.474)	(4.639)	(4.802)
N.obs	2720	2720	2718	2718
Prob >chi2	0.000	0.000	0.000	0.000

Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

* Table I in the Annex presents the complete results, including the sector and country controls

Results in columns 2 and 3 also indicated that young firms have been significantly more affected than older companies.[24] The results of the population-averaged estimator

[24] For the young/older comparison, the coefficient associated to the interaction variable $(t * Young_i)$ represents the difference-in-difference estimate, as defined as:

$$\delta = \left[(g_{Young,t} - g_{Old,t}) - (g_{Young,t-1} - g_{Old,t-1})\right]$$

where $g_{Young,t}$ is the growth sales rate of young companies in the postcrisis period – 2008/2009, and $g_{Young,t-1}$ is the annualized growth sales rate of young companies in the precrisis period – 2004/2007. Similarly, $g_{Old,t}$ and $g_{Old,t-1}$ are the growth sales rate of older firms in the postcrisis and precrisis periods, suggest that the reduction of sales growth performance of young firms was 17.62 percentage points larger than older firms over time (at 10% significance level); the FGLS estimator suggests that this difference was 20.67 percentage points (at 1% significance level). If we consider the results columns 4 and 5, the negative difference for young companies are confirmed.[25]

Also remarkable is the result of the coefficient of the dummy time. The results for this coefficient showed that, when controlling for firm characteristics, sales growth of all companies have presented, on average, a reduction that varies from 47.27 to 54.42 percentage points. This evidence, which showed to be statistically significant at 1% level, could be interpreted as the crisis aggregate impact on the enterprise performance in these countries.

One last feature of Table 3 that is worth mentioning is the result of the coefficient associated to the variable $t * Skill_i$. The results (in columns 2 and 3) showed that sales growth rate of skilled intensive companies (those employing more than 20 percent of workers with university degrees) have increased more than non-skilled firms. From column 2, the population-averaged estimator showed that the sales growth of skilled companies has augmented 12.17 percentage points more than the sales growth of non-skilled firms; from column 3, the population average estimator results points to a difference of 13.08 percentage points in favor of skilled companies over time.[26]

3.2 - Juhn-Murphy-Pierce Decomposition[27]

In order to understand the sources of the difference in sales growth performance between innovative (young) and non-innovative (older) companies, we apply the JMP decomposition technique in two periods, before and after the crisis.

respectively. Since the $Young_i$ variable is defined as a dummy for firms up to five years old *before the crisis* (in 2007), it is worth mentioning that when we compare the sales growth rate of young and older firms, we are actually comparing the performance of firms that, before the crisis, were young (<=5 years old) and older (>= 6 years old). This comparison is then consistent with the innovative/noninnovative comparison as all these firm categories are considered as time-invariant in the model.

[25] Even though young companies have presented larger negative changes of sales growth rate over time, they did grow more than older firms, on average (see result for $Young_i$ variable).

[26] It must be stressed that skilled companies grew less than non skilled firms, on average (see result for $Skill_i$ variable).

[27] This decomposition analysis was performed using Stata (version 11).

For the innovative/non-innovative comparison, the results of the JMP decomposition are listed in Table 5. As the aim of the analyses is to explain the sales growth performance of innovative companies relative to non-innovative firms, the distinct components that explain the sales performance gap between these firm groups (characteristics, return and unexplained effects) are considered from the point of view of innovative companies.

Table 5 shows that, for the pre-crisis period, the total difference between sales growth performance of innovative and non-innovative companies amounts to 13.41 percentage points (in favor of innovative). The observable characteristics effect is also positive implying that the characteristics of innovative firms were actually more favorable than those of non-innovative companies. Turning to the composition of this characteristic effect into the explanatory variables assumed (size, use of skilled labor, export orientation, age, country and sector), we see that, among the firm characteristics, the major contributions for this positive difference came from size (see Table IV in the Annex).

Table 5 – Decomposing the total difference of sales growth rate between innovative and noninnovative firms: JMP results before and after the crisis#*

	Total Difference	Characteristics Effect	Return Effect	Unexplained Effect
Before	13.411	1.038	12.073	0.300
	(5.750)	(0.388)	(0.915)	(0.152)
	100%	7.7%	90.0%	2.2%
After	-1.417	-1.185	-0.250	0.018
	(0.679)	(0.582)	(0.103)	(0.007)
	100%	83.6%	17.7%	-1.3%

The results refer to the sample means of the sales growth rate distribution
* Bootstrap standard error in parentheses

The observable return effect is also positive, revealing that the returns of those characteristics were higher for innovative companies. In other words, it means that the transformation of given "inputs" in results by the innovative firms leaded to higher sales growth rate than the transformation by non-innovative companies, and this accounts for the largest part (90%) of the sales growth gap between the two groups of firms.

Finally, the unexplained components showed to be positive, suggesting that, on average, unobservable factors favor the innovative companies. As mentioned before, we interpret this as an indication of the existence of a positive premium for the entrepreneurship ability, or the "animal spirits", of innovative companies.

In the after-crisis period, Table 5 shows a negative gap between the sales growth performance of innovative and non-innovative companies. This result points out a drastic change in the pattern of comparative sales performance of the two groups of firms when contrasting to the pre-crisis period. What explains this deterioration can be identified when examining the three effects. First, the observable characteristic effect is negative, implying that the characteristics of innovative firms turned to be less favorable than those of non-innovative companies, and this effect accounts for the largest part (83.6%) of the sales growth gap between the two types of firms after the crisis.

The observable return effect is negative as well, indicating that the returns of those characteristics turned to be smaller for innovative companies. On the other hand, the unexplained component remains positive, suggesting that unobservable factors still favor the innovative companies, and served to reduce the sales growth gap between the two firms' categories. Nevertheless, it is also remarkable that this residual was significantly reduced after the crisis, which can be seen as evidence that the "premium" for the ability to innovate ("animal spirits") has declined after the economic downturn.

Table 6 presents the JMP decomposition technique, before and after the crisis, to examine the gap of sales growth performance between young and older companies. As the aim of the exercise is to explain the sales growth performance of young companies relative to older firms, the three effects that explain the sales performance gap between the two groups are considered from the point of view of young companies.

Table 6 – Decomposing the total difference of sales growth rate between young and older firms: JMP results before and after the crisis#*

	Total Difference	Characteristics Effect	Return Effect	Unexplained Effect
Before	19.261 (9.164)	20.985 (7.485)	15.559 (1.491)	-17.283 (6.569)
	100%	109.0%	80.8%	-89.7%
After	-10.696 (3.828)	-4.434 (1.775)	-5.011 (1.005)	-1.252 (0.559)
	100%	41.4%	46.8%	11.7%

The results refer to the sample means of the sales growth rate distribution
* Bootstrap standard error in parentheses

For the pre-crisis period, Table 6 shows that the total difference between sales growth performance of young and older companies is 19.26 percentage points (in favor of young). The observable characteristics effect and the return effect were also positive implying that the characteristics of young firms were actually more favorable than those of older companies, especially regarding use of skilled workforce and export orientation (see Table V in the Annex). The returns of the observable characteristics were higher for younger companies. However, the residual (or unexplained) effect was negative, which we interpreted as evidence that the ability of young firms to benefit from the learning process was inferior to the ability of older companies. This negative effect acted to reduce the positive gap of sales growth between the two groups of firms before the crisis.

In the post-crisis period, the results show a negative gap between the sales growth performance of young and older companies, indicating a reversal of the comparative sales performance of the two groups of firms. The observable characteristic effect have also turned to be negative, which means that, on average, the characteristics of young firms turned to be less favorable than those of older companies after the crisis. If we separate this negative characteristic effect, we see that the major contributions for this result came from size (see Table V in Annex). This could be interpreted as evidence that after the crisis young companies might have faced difficulties evolving into larger firms.

The unexplained component was again negative, suggesting that the ability of young firms to capture the learning benefits remained inferior to the ability of older companies. It is worth mentioning, however, that this residual effect turned to be less negative in the post-crisis period, possibly suggesting that young firms were forced to improve their learning capabilities in order to operate in a more competitive environment. Yet this improvement was not enough to compensate the worse sales growth performance of young enterprises after the crisis.

4 - Conclusions

In this paper we examined the effects of the global downturn on innovative firms and on young firms in order to understand the growth prospects of Eastern European countries using a unique panel data for 1,686 firms in six countries (Bulgaria, Hungary, Latvia, Lithuania, Romania, and Turkey) covering manufacturing, retail and other service sectors. Two empirical methods were used. First, we applied a panel-data analysis in order to assess the difference of sales growth performance between innovative and non-innovative firms, and between young and older firms, over the pre and post-crisis periods, when controlling for certain firm characteristics. Second, we used the Juhn -Murphy-Pierce technique to decompose the difference in sales growth performance between innovative (young) non-innovative (older) companies, over time, into three effects: characteristics effect; returns effect and unexplained effect.

The results show that innovative firms have suffered more than non-innovative companies, regardless the estimator applied (population-averaged estimator or FGLS), and the criteria used to categorize innovation (introduction of a product or a process or development of R&D activities). We also showed that the decrease of sales growth rate of younger firms was more severe than of older companies.

When comparing innovative and non-innovative companies, the decomposition technique showed three main outcomes. First, the positive difference in sales growth performance in favor of innovative companies has been reversed after the crisis. Second, while before the crisis that positive gap in favor of innovative companies was due to their better characteristics, especially regarding size, and, mainly, to higher returns obtained by innovative firms, after the crisis the gap reversion was due mostly to the deterioration of characteristics of innovative companies. Finally, the results showed that the residual (or unexplained) effect was always positive, before and after the crisis, suggesting that the unobservable factors favor the innovative companies, which could also be interpreted as a premium for the entrepreneurship ability, or “animal spirits”, of innovative companies. However, it is also remarkable that this residual was significantly reduced after the crisis, which can be seen as evidence that the “premium” for innovative companies was diminished over time.

When contrasting young and older companies, the use of Juhn-Murphy-Pierce decomposition also revealed three main results. First, we found evidence that the positive gap in sales growth performance in favor of young companies has been reversed after the crisis. Second, the results showed that after the crisis there was a deterioration of the characteristics of the young companies, especially regarding firm size. Finally, the results showed that the residual (or unexplained) effect was always negative, before and after the crisis, suggesting that the ability of young firms to capture the learning benefits was always inferior to the ability of older companies. It is worth mentioning, however, that this residual effect turned to be less negative in the post-crisis period, which can suggest that young firms were forced to improve their learning capabilities in order to operate in a more competitive environment. Nevertheless, this improvement was not enough to compensate the worse sales growth performance of young enterprises after the crisis.

In sum, our results seem to provide robust evidence that innovative and young companies were more affected by the global downturn. Two obstacles for the achievement of pre-crisis growth rates in the region related to this result are a premature exit among young firms and a decline on innovation performance. The exit of potentially viable young firms – assuming the same firm entry rates of the pre-crisis period – and the consequent premature “aging” of the enterprise sector might soften market selection and therefore reduce productivity gains. The impact on innovative firms may hold back investment in R&D among other reasons because lower sales – in a context where diminished access to credit shifted internal funding to finance working capital -- imply less funding for innovation. For those reasons, we interpret our results as indication that the achievement of pre-crisis growth rates in those countries may be difficult.

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Annex

Table I – Explaining the sales growth rate over time: a panel data analysis based on pooled FGLS and FGLS estimators (complete results)

	Innovation measured as introduction of product/process		Innovation measured by the performance of R&D	
	PFGLS estimator	**FGLS estimator**	**PFGLS estimator**	**FGLS estimator**
time	**-47.273*** **	**-47.728*** **	**-48.740*** **	**-54.442*** **
	(3.676)	(4.601)	(3.305)	(4.715)
innovative	14.229**	15.603**	22.022**	5.200
	(6.357)	(6.834)	(9.618)	(7.599)
time X innovative	**-15.975** **	**-16.316** **	**-25.345*** **	**-5.160**
	(6.717)	(6.890)	(9.398)	(7.694)
Young	18.775**	19.490***	18.453**	18.628***
	(9.498)	(7.004)	(9.071)	(7.027)
time X young	**-17.623* **	**-20.679*** **	**-17.446* **	**-19.782*** **
	(10.042)	(7.410)	(9.675)	(7.449)
skilled-intensive	-7.805	-13.336**	-7.538	-11.392**
	(5.970)	(5.343)	(5.475)	(5.030)
Time X skill	12.174*	13.089**	12.431**	10.663**
	(6.288)	(5.540)	(5.960)	(5.190)
Small	6.818**	7.046***	7.703**	7.726***
	(3.337)	(2.528)	(3.193)	(2.503)
Medium	11.141***	11.299***	11.553***	12.059***
	(4.115)	(3.738)	(4.244)	(4.128)
Large	7.243*	11.090***	7.267*	12.064***
	(4.028)	(3.339)	(4.180)	(3.650)
Export-oriented	-6.502*	-4.264	-6.859*	-3.794
	(3.726)	(3.754)	(3.783)	(3.647)
Turkey	10.065**	9.360*	10.096**	9.422*
	(4.942)	(5.342)	(5.040)	(5.436)
Romania	8.942*	7.230	10.515*	7.451
	(5.107)	(6.032)	(5.465)	(6.005)
Hungary	0.203	-1.849	2.001	-1.816
	(2.698)	(2.412)	(3.000)	(2.525)
Latvia	-7.752**	-4.732*	-5.112	-3.412
	(3.420)	(2.743)	(3.340)	(2.738)
Lithuania	-0.695	-0.789	2.254	1.245
	(3.653)	(2.758)	(3.764)	(2.650)
Food	2.668	2.533	3.458	2.942
	(4.218)	(5.636)	(4.179)	(5.501)

#Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table I (cont.) – Explaining the sales growth rate over time: a panel data analysis based on pooled FGLS and FGLS estimators (complete results)

	Innovation measured as introduction of product/process		Innovation measured by the performance of R&D	
	PFGLS estimator	FGLS estimator	PFGLS estimator	FGLS estimator
Textiles	1.348	-7.811	2.000	-8.411
	(5.830)	(7.034)	(5.853)	(6.949)
Garments	-9.075	-11.372**	-8.922	-11.539**
	(5.594)	(5.629)	(5.830)	(5.554)
Chemicals	-5.421	7.410	-4.854	7.999
	(6.616)	(15.012)	(6.719)	(14.841)
Plastic & Rubber	20.910	-5.129	21.586	-5.684
	(17.124)	(8.095)	(17.210)	(8.085)
Non metallic mineral products	-1.372	-7.392	-0.920	-7.294
	(5.335)	(7.223)	(5.815)	(7.148)
Basic metals	-10.436	-1.987	-10.777	-1.359
	(10.691)	(12.759)	(11.436)	(12.927)
Fabricated metal products	-4.404	-9.218*	-5.177	-9.671*
	(4.930)	(5.470)	(4.902)	(5.448)
Machinery and equipments	10.445	6.085	8.265	6.669
	(18.134)	(20.430)	(17.048)	(19.837)
Electronics	11.297*	7.352	11.024*	6.989
	(6.370)	(6.144)	(6.073)	(6.099)
Construction	-4.699	-8.118**	-6.487	-9.877**
	(4.480)	(4.024)	(4.691)	(4.227)
Services of Motor Vehicles	3.904	3.881	4.135	2.683
	(4.900)	(5.693)	(5.165)	(5.671)
Wholesale	5.010	3.351	4.576	4.092
	(4.133)	(4.789)	(4.216)	(4.728)
Retail	8.407*	4.973	8.147*	5.141
	(4.638)	(5.065)	(4.527)	(4.963)
Hotel and restaurants	-5.704	-0.361	-5.446	-0.301
	(5.565)	(5.888)	(5.484)	(5.944)
Transport	6.144	-1.658	4.708	-2.881
	(6.706)	(5.319)	(6.434)	(5.307)
IT	15.981**	5.423	15.371**	5.070
	(7.370)	(5.151)	(6.925)	(5.345)
Other	-7.305	-6.343	-11.015	-6.940
	(11.934)	(9.586)	(13.984)	(9.530)
_cons	12.069**	16.063***	12.097***	21.291***
	(4.734)	(5.474)	(4.639)	(4.802)
N.obs	2720	2720	2718	2718

#Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table II – Explaining the sales growth rate over time with and without export orientation variables: a panel data analysis based on *pooled* FGLS estimator (complete results)

Coefficient	Model 1	Model 2	Model 3
time	-46.844***	-49.193***	-53.399***
	(3.952)	(3.848)	(4.020)
innovative	14.146**	13.723**	
	(6.359)	(6.264)	
time X innovative	-15.891**	-15.530**	
	(6.726)	(6.629)	
Young	18.775**	19.518**	17.988*
	(9.497)	(9.471)	(9.364)
time X young	-17.618*	-18.673*	-16.579*
	(10.041)	(9.993)	(9.992)
skilled-intensive	-7.773	-7.942	-5.863
	(5.972)	(6.034)	(5.418)
time X skill	12.128*	12.047*	9.597*
	(6.286)	(6.312)	(5.825)
Small	6.793**	6.518*	7.785**
	(3.347)	(3.395)	(3.179)
Medium	11.051***	10.186**	12.392***
	(4.163)	(4.097)	(4.057)
Large	7.178*	6.021	8.348**
	(4.043)	(4.027)	(3.868)
Export-oriented	**-5.324**		**-3.238**
	(5.311)		(5.074)
time x export oriented	**-1.813**		**-3.572**
	(5.965)		(5.976)
Turkey	10.086**	8.996*	9.853**
	(4.945)	(4.821)	(4.972)
Romania	9.283*	5.685	8.919*
	(5.394)	(3.959)	(5.395)
Hungary	0.240	0.016	-0.534
	(2.715)	(2.673)	(2.672)
Latvia	-7.712**	-8.069**	-7.144**
	(3.422)	(3.447)	(3.311)
Lithuania	-0.721	-1.016	0.318
	(3.655)	(3.623)	(3.530)
Food	2.726	3.345	2.805
	(4.259)	(4.158)	(4.317)
Textiles	1.319	0.826	-0.369
	(5.824)	(5.827)	(5.975)

#Innovation measured as introduction of product/process; robust standard errors in parenthesis.*** p<0.01, ** p<0.05, * p<0.1

Table II (cont.)– Explaining the sales growth rate over time with and without export orientation variables: a panel data analysis based on *pooled* FGLS estimator (complete results) #

Coefficient	Model 1	Model 2	Model 3
Garments	-9.083	-9.952*	-9.396*
	(5.603)	(5.647)	(5.570)
Chemicals	-5.478	-5.086	-5.636
	(6.596)	(6.742)	(6.513)
Plastic & Rubber	20.916	20.865	19.480
	(17.134)	(17.238)	(16.670)
Non metallic mineral products	-1.312	-1.119	-0.851
	(5.383)	(5.372)	(5.449)
Basic metals	-10.381	-10.544	-9.765
	(10.701)	(10.836)	(11.129)
Fabricated metal products	-4.443	-4.510	-5.991
	(4.900)	(4.932)	(5.002)
Machinery and equipments	10.490	10.782	10.678
	(18.146)	(17.968)	(17.496)
Electronics	11.362*	10.847*	12.026**
	(6.404)	(6.470)	(5.952)
Construction	-4.631	-4.055	-5.748
	(4.507)	(4.416)	(4.533)
Services of Motor Vehicles	3.897	4.373	2.846
	(4.908)	(5.027)	(5.050)
Wholesale	5.053	4.551	5.428
	(4.158)	(4.036)	(4.076)
Retail	8.468*	8.847*	8.192*
	(4.684)	(4.723)	(4.644)
Hotel and restaurants	-5.638	-5.201	-5.657
	(5.593)	(5.513)	(5.466)
Transport	6.162	4.525	4.976
	(6.717)	(6.573)	(6.738)
IT	16.051**	16.619**	17.945**
	(7.393)	(7.424)	(7.596)
Other	-7.322	-7.417	-9.255
	(11.884)	(11.054)	(11.819)
_cons	11.805**	12.735***	17.251***
	(4.955)	(4.725)	(5.451)
N.obs	2720	2720	2730

#nnovation measured as introduction of product/process; robust standard errors in parenthesis *** p<0.01, ** p<0.05, * p<0.1

Table III – Explaining the sales growth rate over time with and without export orientation variables: a panel data analysis based on FGLS estimator (complete results)

Coefficient	Model 1	Model 2	Model 3
time	-47.924***	-48.510***	-55.528***
	(5.114)	(4.622)	(5.026)
innovative	**15.625****	**15.336****	
	(6.825)	(6.728)	
time X innovative	**-16.342****	**-16.109****	
	(6.882)	(6.806)	
Young	19.498***	19.601***	18.713***
	(7.002)	(6.995)	(7.028)
time X young	-20.683***	-20.849***	-19.767***
	(7.409)	(7.390)	(7.456)
skilled-intensive	-13.348**	-13.440**	-11.214**
	(5.357)	(5.383)	(5.032)
time X skill	13.103**	13.080**	10.282**
	(5.551)	(5.540)	(5.122)
Small	7.049***	6.788***	7.819***
	(2.537)	(2.517)	(2.490)
Medium	11.314***	10.585***	12.417***
	(3.748)	(3.378)	(3.900)
Large	11.107***	10.184***	12.755***
	(3.326)	(3.320)	(3.424)
Export-oriented	**-4.688**		**-3.372**
	(6.757)		(6.640)
time x export oriented	**0.694**		**-0.375**
	(6.677)		(6.706)
Turkey	9.339*	8.973*	9.229*
	(5.339)	(5.302)	(5.355)
Romania	7.094	5.315	6.941
	(6.054)	(4.834)	(6.113)
Hungary	-1.859	-1.815	-2.482
	(2.420)	(2.402)	(2.388)
Latvia	-4.738*	-4.952*	-4.002
	(2.746)	(2.771)	(2.657)
Lithuania	-0.785	-0.952	0.886
	(2.762)	(2.768)	(2.657)
Food	2.526	3.151	2.819
	(5.647)	(5.591)	(5.642)

#Innovation measured as introduction of product/process; robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table III(cont.) – Explaining the sales growth rate over time with and without export orientation variables: a panel data analysis based on FGLS estimator (complete results) #

Coefficient	Model 1	Model 2	Model 3
Textiles	-7.797	-8.465	-8.799
	(7.018)	(7.073)	(7.143)
Garments	-11.370**	-11.845**	-11.730**
	(5.628)	(5.642)	(5.628)
Chemicals	7.440	7.643	8.089
	(15.106)	(15.048)	(14.955)
Plastic & Rubber	-5.151	-5.066	-6.059
	(8.116)	(8.030)	(8.005)
Non metallic mineral products	-7.388	-7.669	-7.310
	(7.221)	(7.228)	(7.221)
Basic metals	-2.022	-2.499	-0.940
	(12.789)	(12.683)	(12.938)
Fabricated metal products	-9.206*	-9.436*	-9.832*
	(5.455)	(5.413)	(5.551)
Machinery and equipments	6.092	6.024	7.387
	(20.429)	(20.420)	(19.979)
Electronics	7.335	7.128	7.548
	(6.148)	(6.268)	(5.910)
Construction	-8.147**	-7.214*	-9.662**
	(4.082)	(3.850)	(4.267)
Services of Motor Vehicles	3.867	4.619	2.648
	(5.710)	(5.865)	(5.803)
Wholesale	3.331	3.542	4.202
	(4.828)	(4.779)	(4.792)
Retail	4.945	5.820	5.081
	(5.115)	(5.363)	(5.125)
Hotel and restaurants	-0.398	0.351	-0.509
	(5.930)	(5.907)	(6.064)
Transport	-1.684	-2.131	-2.855
	(5.337)	(5.295)	(5.375)
IT	5.411	6.006	5.917
	(5.166)	(5.069)	(5.088)
Other	-6.305	-5.874	-7.071
	(9.551)	(9.569)	(9.596)
_cons	16.186***	15.887***	22.577***
	(5.836)	(5.488)	(5.651)
N.obs	2720	2720	2730

#Innovation measured as introduction of product/process; robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table IV – Decomposing the total difference of sales growth rate between innovative and noninnovative firms: JMP results before and after the crisis

	Total Difference	Total characteristics Effect	*specific characteristics effects*						Returns Effect	Unexplained Effect
			skill	*age*	*size*	*export*	*country*	*sector*		
Before	13.411	1.038	*-1.518*	*-0.358*	*0.704*	*-0.441*	*2.122*	*0.529*	12.073	0.300
After	-1.417	-1.185	*0.641*	*-0.103*	*0.612*	*-0.002*	*-2.625*	*0.292*	-0.250	0.018

Table V - Decomposing the total difference of sales growth rate between young and older firms: JMP results before and after the crisis

	Total Difference	Total characteristics Effect	*Specific characteristics effects*						Returns Effect	Unexplained Effect
			skill	*innovation*	*size*	*export*	*country*	*sector*		
Before	19.261	20.985	*17.284*	*-0.228*	*-1.197*	*0.351*	*4.936*	*-0.160*	15.559	-17.283
After	-10.696	-4.434	*1.658*	*0.212*	*-1.707*	*0.235*	*-4.207*	*-0.625*	-5.011	-1.252